Analysis of Electricity Price Characteristics Based on GARCH-M Model with Skewed Student-t Distribution

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***Abstract*-Analysis of electricity price characteristics is crucial to understand the behaviour of derivatives pricing and to quantify the risk in electricity markets. In this paper, a multi-cycle GARCH-M model with skewed student-t distribution for residuals, which is solved by maximum likelihood estimation, is proposed. The model can explicitly address the relationship with system loads, heteroskedasticities, seasonalities, time-varying skewnesses and heavy-tails of electricity prices. The empirical analysis based on the historical data of the PJM electricity market shows that the conditional variance and system load have a significant effect on average daily electricity prices, and there are volatility clustering and weekly, semi-monthly, monthly, bimonthly, quarterly and semi-annual periods, and the variances and heavy-tails of electricity prices manifest clearly time-varying characteristics. The model holds parsimonious scale of estimated parameters, less computational costs, high practical application value, and it's easy to select the orders.**

Keywords-skewed student-t distribution; skewness and fat-tail; multi-cycle; volatility clustering; GARCH-M model

I. INTRODUCTION

With the rapid growth of derivative securities in electricity markets, the modelling and management of price risk have become important topics for researchers and practitioners. Electricity price is set by the market clearing price at which quantity supply is equal to quantity demand. It is influenced not only by the objective factors such as climates, loads, power generating costs, available generation capacities and network congestions, but also by the subjective factors such as market trading rules, participants' bidding strategies and their psychological reactions to price changes. All of these factors which make an accurate price forecast become a complex issue. The current methods to predict electricity price can be divided into long- and short-term forecasting methods [1]. The long-term electricity price forecasting can be achieved by simulating the competition rules, which mainly includes oligopoly equilibrium model, probabilistic production simulation and intelligent agent simulation. With the statistical analysis for historical data, the mathematical model to reflect price changes can be established and the short-term price forecasting can be obtained. The short-term forecasting methods mainly include time series analysis (TSA), artificial neural networks (ANNs) and grey system forecasting models.

ANNs have been widely used for nonlinear multivariate problems because of the adaptive ability to uncertain fuzzy systems [2-10]. In [2,3], the electricity spot prices in Victoria, Spain and California markets were predicted by three layered feedforward ANNs based on the training methods of back propagation and Levenberg-Marquardt algorithms. In [4,5], the performance of Gaussian radial basis function ANNs (GRFANNs) and the traditional ANNs were compared indicting superior performance of the GRFANNs with faster learning speed and better approximation capability, and the GRFANNs are more suitable for short-term electricity price forecasts. In [6-10], the approaches of forecasting short-term electricity prices using combination of fuzzy logic, Kalman filter, support vector machines and ANNs were proposed respectively, the results show that significantly improved prediction performance can be achieved by using the hybrid forecasting methods. However, the lower learning speed and the parameters which are not flexible to be adjusted have impeded their application in practice.

With relatively small historical data required, TSA can accurately reflect the continuous changes of the historical data. Autoregressive moving average (ARMA) and ARMA with exogenous variables (ARMAX) models are the commonly used TSA methods. In [11], an ARMAX model with load as an exogenous explanatory variable was used to predict the next 24-hour spot price in the PJM electricity markets. Considering the non-constant mean and variance for most electricity price time series, an electricity price forecasting method based on autoregressive integrated moving average (ARIMA) model has been proposed in [12], but the impacts of load and other factors were not considered. Cuaresma et al. [13] have noted that each hour of days is also an important factor to influence electricity prices and an ARMA-based period-decoupled forecasting model was proposed, showing greatly improved prediction accuracy for the price spikes. The electricity price forecasting methods which combine ARIMA with predicted errors improvement and wavelet transfer function were respectively proposed in [14] and [15]. A period-decoupled electricity price forecasting method based on transfer function models, taking the effect of load on electricity price and the non-stationary properties of price series into account, was presented in [16], and further improved the prediction accuracy. However, with the assumption that the price distribution is normal with constant variance, these models can not effectively deal with the seasonalities, heteroscedasticities, heavy-tails of electricity prices, and the more computational costs and estimated parameters have also impeded their heavy use in practice.

Compared with normal distribution, there are positive skewness and excess kurtosis for electricity price series. In evaluating the price risk in electricity market, we should take the positive skewness and excess kurtosis into account. With comprehensive analysis of the basic features and influencing factors of electricity price, a multi-cycle GARCH-M model

with skewed student-t distribution for residuals (thereafter, st-GARCH-M) is proposed, in which the heteroscedasticities, seasonalities, kurtosises and heavy-tails, volatility-clustering and relationship to system loads are jointly addressed. The model holds the advantages of less computational cost and parsimonious scale of estimated parameters. The numerical example based on the historical data of the PJM market shows that the conditional variance and system load have significant effects on the average daily electricity prices, and there are volatility clustering and weekly, semi-monthly, quarterly and semi-annual periods, and the variance of electricity price series and the degree of freedom of skewed student-t distribution manifesting the clear time-varying characteristics.

II. MODEL AND SOLUTION METHOD

A. Multi-Cycle St-GARCH-M Model

Electricity price forecasting model can be viewed as a multi-input single-output system, in which the output variable is the electricity price and the input variables are the impact factors of electricity price such as fuel prices, seasonality, climate, load and bidding strategies of market participants. Moreover, in this paper, the system will be delineated by a multi-cycle st-GARCH-M model. The market clearing prices and system loads are publicly available in each market all over the world. Therefore, the system loads at hours t, t-1, and the electricity prices at hours t-1, t-2, are selected as the input variables. Assuming that p_t , d_t , ε_t and z_t denote the electricity spot price, the system load, the residual and the standardized residual at hour t, then the multi-cycle st-GARCH-M model can be formulated as:

$$
\begin{aligned}
p_t &= f(t) + \gamma(B)d_t + \varphi(B)p_t \\
&\quad + \theta(B)\sqrt{h_t} + \kappa(B)\varepsilon_t \\
\varepsilon_t &= \sqrt{h_t}z_t, \varepsilon_t \left| I_{t-1} \sim D(0,h_t), z_t \right| I_{t-1} \sim D(0,1) \\
h_t &= \beta_0 + \sum_{i=1}^{r_h} \beta_{1i}h_{t-i} + \sum_{i=1}^{s_h} \beta_{2i}\varepsilon_{t-i}^2 \\
f(t) &= \alpha_0 + \alpha_1 t + \alpha_2 d_{wkd} \\
&\quad + \sum_{i=1}^{m} \alpha_{1i} \sin\left((\frac{2i\pi}{365}t + \alpha_{2i}) \right) \\
\gamma(B) &= \gamma_0 + \gamma_1 B + \gamma_2 B^2 + \cdots + \gamma_u B^u \\
\varphi(B) &= \varphi_1 B + \varphi_2 B^2 + \varphi_3 B^3 + \cdots + \varphi_p B^p \\
\theta(B) &= \theta_0 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_v B^v \\
\kappa(B) &= 1 + \kappa_1 B + \kappa_2 B^2 + \cdots + \kappa_q B^q
\end{aligned}
\tag{1}
$$

where B is the backshift operator, m denotes the changing cycles of electricity price series per year, u , v , p and q represent respectively the lagged orders of d_t , $\sqrt{h_t}$, p_t and ε_t in the mean equation, r_h and s_h denote the lagged order of h_t and ε_t^2 in the conditional variance equation, I_{t-1} denotes an available information set till period $t-1$, h_t denotes conditional variance of ε_t , $f(t)$ denotes the time trend and seasonal changes, d_{wkd} is a dummy variable that takes a value of 1 if the observation is in weekday and zero otherwise, $\alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_{11}, \cdots, \alpha_{1m}, \alpha_{21}, \cdots, \alpha_{2m})$, $\gamma=(\gamma_1,\cdots,\gamma_u)$, $\varphi = (\varphi_1, \cdots, \varphi_p)$, $\kappa = (\kappa_1, \cdots, \kappa_q)$, $\theta = (\theta_1, \cdots, \theta_v)$ and $\beta=(\beta_0,\beta_{11},\cdots,\beta_{1r_h},\beta_{21},\cdots,\beta_{2s_h})$ are the estimated parameters. With this general formulation for the sinusoidal function we allow for the possibility of having many cycles per year, and the amplitude and location of the peak of the ith cycle can be respectively captured by α_{1i} and α_{2i} . $\beta_0 > 0$, $\beta_{1i}, \beta_{2j} \geq 0$, $\forall i \in [1, r_h], j \in [1, s_h]$ are needed to guarantee the strictly positive for the conditional variance and the process not to degenerate.

B. Parameters Calibration

Before parameters calibration, assumption on the distribution of residuals needs to be made. Assuming that the probability density function (PDF) for the standardized residual z_t is consistent with skewed student-t distribution, the conditional PDF of ε_t can be expressed as [17]:

$$
\begin{aligned}
& g(\varepsilon_t | I_{t-1}) = \frac{1}{\sqrt{h_t}} g(z_t | I_{t-1}) \\
& g(z_t | I_{t-1}) = b_t c_t \left(1 + \frac{1}{(\eta_t - 2)} \left(\frac{b_t z_t + a_t}{1 \pm \lambda_t} \right)^2 \right)^{-\frac{\eta_t + 1}{2}} \\
& 1 \pm \lambda_t = \begin{cases} 1 + \lambda_t & z_t \geq -a_t/b_t \\ 1 - \lambda_t & z_t < -a_t/b_t \end{cases} \\
& a_t = 4\lambda_t c_t \left(\frac{\eta_t - 2}{\eta_t - 1} \right) \\
& b_t^2 = 1 + 3\lambda_t^2 - a_t^2 \\
& c_t = \Gamma(\frac{\eta_t + 1}{2}) \Big/ \left(\sqrt{\pi(\eta_t - 2)}\Gamma(\frac{\eta_t}{2}) \right)
\end{aligned}
\tag{2}
$$

where Γ is a Gamma function, λ_t and η_t are the conditional skewness and degree of freedom corresponding to the skewed student-t distribution of z_t , respectively, and can be calculated by:

$$
\begin{aligned}
& \eta_t = L_\eta + \frac{U_\eta - L_\eta}{1 + \exp(-\omega_t)} \\
& \omega_t = \delta_0 + \sum_{i=1}^{r_\eta} \delta_{1i}\varepsilon_{t-i} + \sum_{i=1}^{s_\eta} \delta_{2i}\varepsilon_{t-i}^2 \\
& \lambda_t = L_\lambda + \frac{U_\lambda - L_\lambda}{1 + \exp(-\tau_t)} \\
& \tau_t = \mu_0 + \sum_{i=1}^{r_\lambda} \mu_{1i}\varepsilon_{t-i} + \sum_{i=1}^{s_\lambda} \mu_{2i}\varepsilon_{t-i}^2
\end{aligned}
\tag{3}
$$

where U_η and L_η denote the upper and lower limits of η_t , r_η and s_η are respectively the lagged order of ε_t and ε_t^2 in the conditional freedom degrees equation, U_λ and L_λ denote

the upper and lower limits of λ_t, r_λ and s_λ are respectively the lagged order of ε_t and ε_t^2 in the conditional skewness equation, $\delta = (\delta_0, \delta_{11}, \cdots, \delta_{1r_\eta}, \delta_{21}, \cdots, \delta_{2s_\eta})$ and $\mu=(\mu_0,\mu_{11},\cdots,\mu_{1r_\lambda},\mu_{21},\cdots,\mu_{2s_\lambda})$ are the parameters to be estimated.

Let $\xi = (\alpha, \varphi, \theta, \gamma, \kappa, \beta, \delta, \mu)$, the log-likelihood function for all observations corresponding to ε_t is given by:

$$L(\xi) = \sum_{t=1}^{n} l_t(\xi) = \sum_{t=1}^{n}\left(\ln\left(\frac{b_t c_t}{\sqrt{h_t}}\right) - \frac{\eta_t+1}{2}\ln\left(1+\frac{1}{(\eta_t-2)}\left(\frac{b_t z_t + a_t}{1\pm\lambda_t}\right)^2\right)\right) \tag{4}$$

where $l_t(\xi) = \ln g(\varepsilon_t | I_{t-1})$ is the log-likelihood function for one observation at period t. By maximizing the $L(\xi)$, the estimate values of parameters ξ , $\hat{\xi}$ can be obtained. It is important to note that the log-likelihood function $L(\xi)$ is highly nonlinear. Therefore the starting values of the parameters ξ must be selected with care. In order to improve the accuracy of estimation, a successive approximation method, namely using the parameters estimated from simpler models as starting values for more complex one, is used in this paper.

C. Model Checking

Under large sample, the distribution of the maximum likelihood estimation $\hat{\xi}$ can be approximated by normal distribution:

$$\hat{\xi} \sim N\left(\xi_0, \left[-\mathbf{H}(\xi_0)\right]^{-1}\right) \tag{5}$$

where ξ_0 is the truth values of the estimated parameters ξ, $\mathbf{H}$ is a Hessian matrix. A consistent estimate of $\mathbf{H}(\xi_0)$ can be obtained by evaluating $\partial L(\xi) / \partial\xi\partial\xi'$ at $\hat{\xi}$. After calculating the variance of $\hat{\xi}$, the significance of estimated parameters can be tested using t-statistics.

The Nyblom-statistic, holding the advantage that its asymptotic distribution only depends on the number of estimated parameters, is used to test the constancy of the proposed model [18]. The Nyblom-statistic W_N can be expressed as:

$$W_N = \frac{1}{n}\sum_{t=1}^{n}\mathbf{S}_t'\mathbf{V}^{-1}\mathbf{S}_t \tag{6}$$

where

$$\mathbf{S}_t = \sum_{i=1}^{t}\frac{\partial l_t(\xi)}{\partial\xi}\bigg|_{\xi=\hat{\xi}}$$

$$\mathbf{V} = \frac{\partial L(\xi)}{\partial\xi}\left(\frac{\partial L(\xi)}{\partial\xi}\right)'\bigg|_{\xi=\hat{\xi}}$$

The Nyblom-statistic can be also used to test the constancy of a single estimated parameter. The Nyblom-statistic $W_{N,k}$ corresponding to the kth estimated parameter is given by:

$$W_{N,k} = \frac{1}{n}\sum_{t=1}^{n}\frac{S_{kt}^2}{V_{kk}} \tag{7}$$

where S_{kt} is the kth element of $\mathbf{s}_t$, V_{kk} is the kth diagonal element of $\mathbf{V}$.

Cramer-Von Mises statistic can be used to test if the distribution of residuals is consistent with skewed student-t distribution. Let $F_N(z)$ denote the cumulative distribution function (CDF) of skewed student-t, $F(z)$ denote the actual CDF of the residuals. Then Cramer-Von Mises statistic can be formulated as:

$$W_{CVM} \approx \sum_{t=1}^{n}\left(F_N(z_t) - F(z_t)\right)^2 \tag{8}$$

D. Forecasting Accuracy Evaluation

Generally speaking, the electricity price forecasting model is one with time-varying parameters, and its parameters should be modified by the new available data in order to improve the forecasting accuracy. In this paper, the mean absolute percentage error (MAPE) is used to evaluate the forecasting accuracy. It can be calculated as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|\hat{p}_t - p_t\right|}{p_t} \tag{9}$$

where $\hat{p}_t$ and p_t respectively refer to the forecasted and actual realized electricity prices at period t , and n is the period number to be forecasted.

III. EMPIRICAL RESULTS

The PJM is organized as a day-ahead market. Participants submit their buying and selling bid curves for each of the next 24 hours. Then the market operator aggregates bids for each hour and determines market clearing prices and volumes for each hour of the following day. In this paper, A total of 1197 observations of average daily electricity spot prices in dollars per megawatt hour (\$/MWh) and average daily loads in gigawatt (Gw) are employed to validate the performance of the multi-cycle st-GARCH-M model. The sample period begins on 1 Jun., 2007 and ends on 9 Sep., 2010. Table 1 presents some descriptive statistics for the average daily electricity spot price and load series. It can be seen from Table 1 that electricity prices and loads are quite volatile, highly abnormal, clearly skewed rightward, and with a median well below the mean. In fact the nulls of normality of electricity price and load series are rejected with the Jarque-Bera test. This is typical for electricity spot prices in a competitive market.

By analysing the correlation coefficient, partial correlation coefficient and time trend chart of the sample data, the values of $m, p, q, u, v, r_h, s_h, r_\eta, s_\eta, r_\lambda, s_\lambda$ in the multi-cycle st-GARCH-M model can be identified. In our situation, they are equal to

52, 7, 3, 1, 0, 1, 1, 1, 1, 1, 1. Table 2 shows the results of the maximum likelihood estimation (except for the coefficients of intercept and conditional skewness, all other coefficients that are not significant at the 95% confidence interval have been removed). Investigating the data in Table 2, the following conclusions can be derived:

TABLE I DESCRIPTIVE STATISTICS OF THE SAMPLE DATA

Statistics	Price($/MWh)	Load(GW)
Mean	53.52041	81.19221
Median	49.97068	79.89221
Maximum	189.6557	115.7839
Minimum	24.87494	58.34586
Std. Dev.	20.20158	10.50560
Skewness	1.420081	0.375318
Jarque-Bera (p-value)	1046.748 (0.0000)	36.78506 (0.0000)

TABLE II ESTIMATION RESULTS OF GARCH-M-ST MODEL

Parameters	Estimated	Std. Err.	t statistics	P value	Nyblom statistics
α_0	-1.3102	0.7862	-1.666	0.0956	0.0660
α_2	-1.9915	0.3278	-6.074	0.0000	0.1313
γ_0	0.9377	0.0293	32.006	0.0000	0.0758
γ_1	-0.8899	0.0268	-33.146	0.0000	0.0595
φ_1	0.9424	0.0125	75.254	0.0000	0.0635
φ_7	0.0281	0.0088	3.195	0.0014	0.0697
α_{12}	-0.4977	0.1192	-4.175	0.0000	0.0304
α_{22}	-0.1629	0.0446	-3.653	0.0003	0.1020
α_{14}	-0.2069	0.0801	-2.583	0.0098	0.1778
α_{24}	1.0293	0.1449	7.105	0.0000	0.1045
α_{124}	362.29	3.1787	113.97	0.0000	0.0341
α_{224}	-234.40	4.0323	-58.130	0.0000	0.0346
α_{152}	-81.715	0.9176	-89.056	0.0000	0.0516
α_{252}	-94.889	0.1796	-528.44	0.0000	0.2991
κ_1	-0.2360	0.0318	-7.426	0.0000	0.1541
κ_2	-0.2530	0.0321	-7.874	0.0000	0.0899
κ_3	-0.1470	0.0296	-4.959	0.0000	0.2236
θ_0	0.0639	0.0315	2.032	0.0422	0.1576
β_0	0.2601	0.1164	2.236	0.0254	0.1292
β_{11}	0.8286	0.0253	32.814	0.0000	0.4837
β_{21}	0.2099	0.0375	5.600	0.0000	0.5081
δ_0	-2.0287	0.3834	-5.291	0.0000	0.1355
δ_{11}	0.3812	0.0907	4.203	0.0000	0.0275
δ_{21}	0.0139	0.0046	3.036	0.0024	0.0530
τ_0	0.5999	0.1053	5.699	0.0000	0.1360
τ_{11}	-0.0178	0.0187	-0.951	0.3414	0.1219
τ_{21}	0.0001	0.007	0.078	0.9380	0.0252
Maximum Log-likelihood	-2.7852		MAPE		6.308%
Cramer-Von Mises Statistics	0.1651		Nyblom Statistics		8.3773

1）The MAPE 6.308% of the st-GARCH-M model is approximately equal to the proposed models in [11-16], but the number of estimated parameters is only 27, which is less than the number of the proposed models in [11-16]. To some extent this reduces complexity, improves the computing speed, and strengthens the practical application ability of the model.

2) The t-statistics for $\alpha_{1i}, \alpha_{2i}, i \in (2, 4, 24, 52)$ are significant at the 99% confidence level. This shows that there are weekly, semi-monthly, quarterly and semi-annual cycles in the sample periods. The amplitudes of the peak for the weekly and semi-monthly cycles are larger than the others.

3) The t-statistic for α_2 is significant at the 99% confidence level. This shows that the impacts of load on the average daily electricity prices for weekday and weekend are more different.

4) The t-statistics for γ_0 and γ_1 are significant at the 99% confidence level, indicating that d_t has a marked impact on the average daily electricity prices. However, when d_t is incorporated in the mean equation, the sign of α_2 changes from positive to negative, showing that there are some substitution effects between d_{wkd} and d_t. Moreover, when d_t is replaced by d_t^2 in the mean equation, the MAPE is reduced from 6.308% to 6.16%, indicating that the relationship of load and electricity price may be more accurately described by d_t^2.

5) The t-statistic for β_{11} in the conditional variance equation is positive and significant at the 99% confidence level, indicating that the volatility of electricity price series are strongly persistent. The impacts of prior period volatility on current period volatility show a gradually weakening trend. As shown in Figure 1, clearly there are volatility clustering, demonstrating that high conditional variance is followed by high conditional variance.

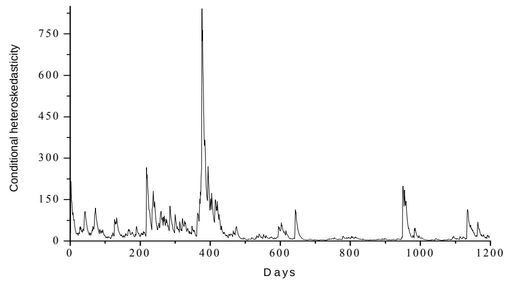

Fig. 1 conditional heteroskedasticity of price series

6) The t-statistic of β_{21} in the conditional variance equation is significant at the 99% confidence level, indicating that the volatility of electricity price series will be strengthened by external shocks. The sum of β_{11} and β_{21} is close to 1, indicating that there may be an integrated GARCH effect for the average daily electricity price series. The impacts of volatility of prior periods and external shocks on the current period volatility have longer persistence.

7) The t-statistic for θ_0 is significant at the 95% confidence level, showing the conditional variance has a marked impact on the average daily electricity prices. When

keeping the other explanatory variables constant, the average daily electricity prices increase with the increase of the volatility of prices series.

8) The t-statistics of δ_{11} and δ_{21} are significant at the 99% confidence level, indicating that the conditional degree of freedom manifests obviously time-varying features. The residuals and their squares exert a significant impact on the conditional degree of freedom of student-t distribution. The PDF of conditional degree of freedom is depicted in Figure 2. It can be seen that conditional freedom degrees are mainly between 2 and 8, indicating that obviously there are fat-tail in the electricity price series.

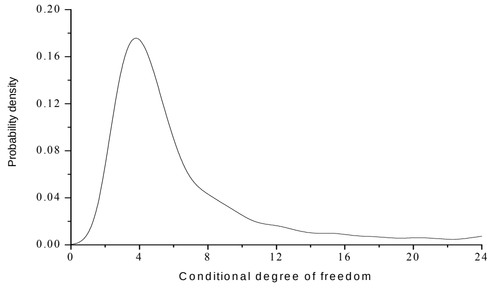

Fig. 2 probability density of degree of freedom

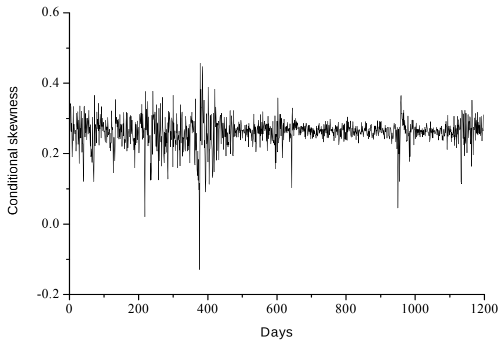

Fig. 3 Conditional skewness of residuals

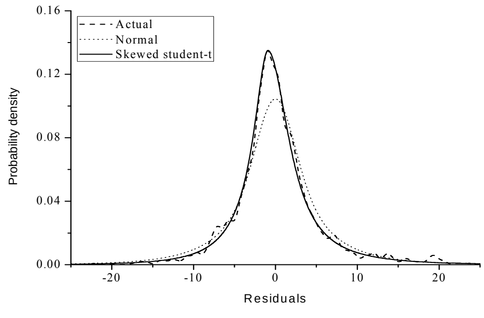

Fig. 4 Probability density of residuals

9) The t-statistic of τ_0 is positive and significant at the 99% confidence level, but the t-statistics of τ_{11} and τ_{21} are not significant at the 90% confidence level, indicating that in the sample periods the electricity price series are clearly skewed rightward, and can be described by homogeneous skewness. As shown in Figure 3, they are mainly between 0.2 and 0.32.

10) The Cramer-Von Mises statistic is less than the critical limit at the 99% confidence level, indicating that the skewed student-t distribution is fully consistent with the actual distribution of residuals, as shown in Figure 4.

11) The Nyblom-statistics of all estimated parameters are less than the critical limit at the 99% confidence level, but the Nyblom-statistic for the whole model is slightly larger than the critical limit at the 99% confidence level, indicating that there are some instabilities for the above model. When removed d_{wkd} or d_t from the mean equation, the Nyblom-statistic of the whole model will be less than the critical limit at the 99% confidence level. One possible explanation is that there are some substitution effects between d_{wkd} and d_t. So the way to address the two influencing factors, d_{wkd} and d_t more reasonably, will be the main problem to be solved in the future research work.

IV. CONCLUSIONS

With comprehensive analysis of the basic features and influencing factors of electricity price, a multi-cycle st-GARCH-M model is proposed, in which the heteroscedasticity, skewness, kurtosis and fat-tail, and seasonalities of electricity price series are dealt with time-varying variance, time-varying skewness, time-varying degree of freedom and sinusoidal function respectively. The model holds the advantages of less computational cost and parsimonious scale of estimated parameters. Moreover, the time trend and the relationship between load and spot price can also be taken into account. The numerical example based on the historical data of the PJM electricity market shows that the conditional variances and system loads have significant effects on the average daily electricity prices, and there are volatility clustering and weekly, semi-monthly, quarterly and semi-annual periods, and the variance of electricity price series and the degree of freedom of skewed student-t distribution manifest the clear time-varying features. However, the substitution effect between d_{wkd} and d_t in the mean equation may bring about some instability for the proposed model. So how to more reasonably address the relationship among load and spot price and further improve the goodness of fit of the proposed model is a relevant subject for future research work.

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